

# Grounded Lexicon Acquisition - Case Studies in Spatial Language

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**Abstract**—This paper discusses grounded acquisition experiments of increasing complexity. Humanoid robots acquire English spatial lexicons from robot tutors. We identify how various spatial language systems, such as projective, absolute and proximal can be learned. The proposed learning mechanisms do not rely on direct meaning transfer or direct access to world models of interlocutors. Finally, we show how multiple systems can be acquired at the same time.

## I. INTRODUCTION

There is an ongoing debate how conceptual development and linguistic development interact. On the one hand, there is the idea that many parts of the human conceptual repertoire are pre-determined by biological constraints. While certainly, biological constraints play an important role for linguistic development both ontogenetically and phylogenetically, recent evidence points to considerable flexibility on the conceptual and linguistic level [1]. The evidence for this comes from studies in linguistic diversity, which show tremendous cross-linguistic variation on the syntactic, semantic and conceptual level [2], [3]. For instance, while English has an elaborate system of projective categories such as “front” and “back”, other languages such as Tzeltal [4] rely on absolute geocentric features in the environment to build conceptual spaces.

Lexicon acquisition by artificial systems is an important topic and has been treated in a number of studies [5]–[8]. Also in the ICDL/Epirob community this is a recurring theme that has received considerable attention (e.g. see [9], [10] for recent examples). However, many of these studies are done in pure simulation, or presuppose shared meaning spaces and/or shared world models. Another simplification often made is to use discrete or discretised meaning spaces. This paper tries to remedy this situation and explores what are the necessary computational mechanisms allowing artificial agents to acquire grounded spatial lexicon systems that can be used both in language understanding and language production. Learners directly operate on continuous perceptual spaces and conceptual development is directly organising the sensorimotor space.

We setup experiments with humanoid robots in which a tutor robot is teaching a learner robot spatial relations in progressively more and more complex tasks. We start by exploring the acquisition of single spatial relation systems (e.g. only proximal relations such as “near” and “far”). Subsequently, we move to the simultaneous acquisition of different category systems. Finally, we discuss systems which are flexible enough

to acquire any kind of category system without a priori assumptions about the systems themselves.

This paper is part of a larger research effort that tries to understand the basic processing principles [11], acquisition and evolution of spatial language [12] with a particular focus on linguistic variation. Here we focus on lexicon acquisition. We exemplarily carry out acquisition experiments for English, which features different spatial relation systems that represent rather completely the different types of systems we find in different combinations also in other languages.

## II. EXPERIMENTAL SETUP

We use *language games* [13] – routinised interactions between communication partners. In our case, Sony humanoid robots interact in an office environment. Always two robots interact. One is a tutor agent, the other is a learner. Before an interaction, robots are scanning the environment for objects. Each robot’s vision system singles out objects such as coloured blocks, marker-augmented boxes and wall-pasted markers from the environment and estimates object properties such as distance, angle and color [14]. Figure 1 shows the experimental setup and the objects involved.

An interaction begins with random assignment of roles to the learner and the tutor. One is the speaker, the other acts as the hearer. The interaction then proceeds with the following steps.

- 1) The speaker selects one object from his world model, further called the topic  $t$ . For the purpose of this paper only blocks are chosen (yellow objects in Figure 1).
- 2) The speaker tries to find a spatial relation for describing the topic.
- 3) The speaker looks up the word associated with this spatial relation in memory and produces the word.
- 4) The hearer looks up which relation is associated with this word in memory and examines his world model to find out whether there is a unique object which satisfies this relation.
- 5) The hearer then points to this object in the world.
- 6) The speaker checks whether the hearer selected the same object as the one the speaker originally chose. If they are the same, the game is a success and the speaker signals this outcome to the hearer.
- 7) If the game is a failure, the speaker points to the topic.

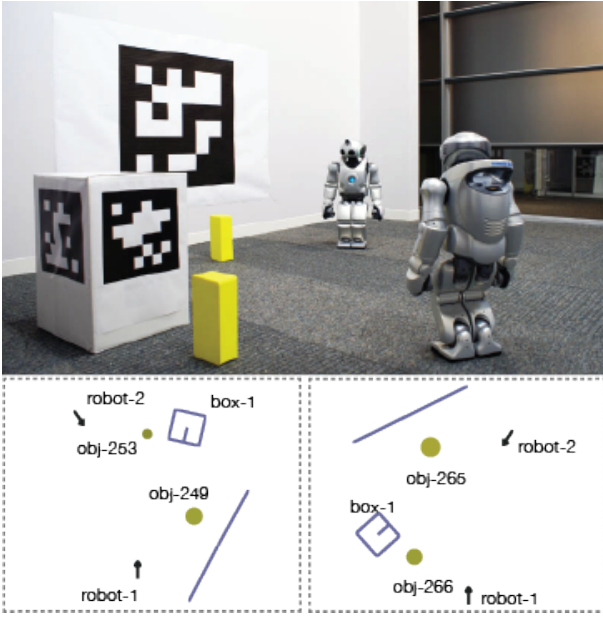


Fig. 1. Spatial language game setup. The world models computed by each robot are shown left and right. Each robot estimates the position of objects from his own perspective. The arrows signify position and orientation of the robots. Each robot is himself at the center of the coordinate system (robot-1). The blue line in each world model represents the global direction marker on the wall. Yellow circles represent colour and position of the bricks in the scene. The blue rectangle shows position and orientation of the box (not important for this paper).

This script explicitly defines the feedback and input the learner deals with. He gets linguistic feedback (if he is hearer), positive or negative feedback and pointing. Never is there any direct meaning transfer or world model sharing between the tutor and the learner. In fact, the world models of tutor and learner are always necessarily different because the world is perceived by each agent separately [15].

Importantly, tutor and learner take on roles as speaker and hearer randomly. This means that learners immediately start trying to speak themselves even though the command of the language they are learning might be rudimentary. Consequently, interactions can fail in various ways. For instance, the learner (as a speaker) might be unable to find a spatial relation for discriminating the topic (step 2), or the learner (as a hearer) might not know the spatial term (step 4). Moreover, the hearer (tutor or learner) might point to the wrong object (step 5).

### III. REPRESENTING SPATIAL CATEGORIES

The English locative system can be broadly categorised into three different classes of categories.

*Proximal categories:* such as “near” and “far” rely on proximity to some particular landmark object.

*Projective categories:* are categories such as “front”, “back”, “left” and “right”. These categories are primarily angular categories signifying a direction. The landmark object provides a special direction “the front”. All other categories follow from this pivot direction. The projective system mostly relies on object features to determine which is the front. This is called intrinsic frame of reference in the literature (we are

ignoring the relative frame of reference in this paper). In this experiment the robots use their own front for determining the pivot direction.

*Absolute categories:* such as “north”, “south”, “east” and “west” rely on a compass directions, with the pivot direction to the magnetic north pole. The absolute system relies on features of the environment to determine the layout of the angles. In other languages, other geocentric features of the environment are used. For example, in Tenejapan the directions uphill/downhill are used [4]. In the experiments discussed here, the wall marker is used as a global direction on the scene.

We represent spatial categories using a either prototypical angle (absolute, projective) or distance (proximal). Additionally, each category is parameterised by a  $\sigma$  value. The two parameters to a category, prototype value and  $\sigma$ , describe the similarity function of the category.

$$\text{sim}_a(o, c) := e^{-\frac{1}{2\sigma_c} d_a(o, c)} \quad (1)$$

where  $o$  is some object,  $c$  a category and  $d_a$  is a distance function defined between prototypes and objects. Distance functions are defined for angle  $d_a$  and proximal  $d_p$  categories separately. Below is the definition of angular distance  $d_a$  and proximal distance  $d_p$

$$d_a(o, c) := |a_o - a_c| \quad (2)$$

$$d_p(o, c) := |d_o - d_c| \quad (3)$$

where  $a_o$  is the angle to a particular object  $o$  and  $a_c$  is the prototypical angle of category  $c$ . For example, for “front” the angle  $a_c = 0.0$  where 0.0 is the front side of the reference object.  $d_o$  is the distance to object  $o$  and  $d_c$  is the prototypical distance of the category  $c$ .

Notice that both angular and proximal distances are always defined relative to a coordinate system origin. By default this is the robot observing the world. However, robots can change perspective to other objects, including other robots using their world model as basis for the transformation.

Similarity is important because it guides speakers and hearer in the identification referents of interactions. A speaker chooses the category that maximises similarity to the topic while having low similarities with all other objects in his world model. The hearer will choose the object as referent which has the highest similarity with the category, he thinks the speaker is using.

### IV. ACQUISITION OF SPATIAL CATEGORIES

Acquisition of a category is a two-step process. It starts with the learner encountering a new word in a particular communicative situation. The learner will store the new word and the category it represents in his memory. We call this *adoption*. The information available to the learner in a single interaction is typically insufficient for a good estimate of the spatial category. The learner will therefore integrate information from subsequent interactions in which the new word is used. We call this process *alignment*.

Categories are initially adopted by a learner in a particular interaction using the following operation, which has two parts. The learner monitors processing and diagnoses if there was a problem. If there was a problem, he tries to repair it.

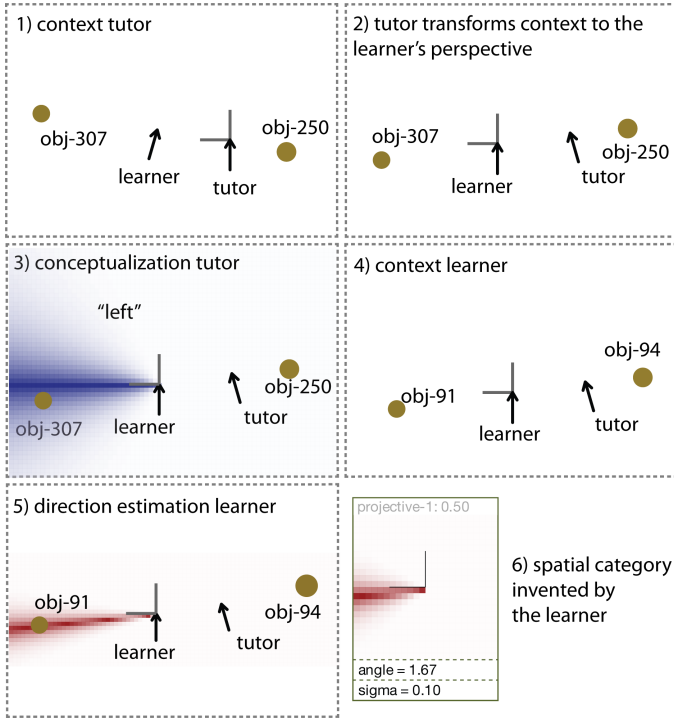


Fig. 2. This figure details the adoption of an unknown category label by a learner agent in interaction with a tutor agent. The tutor who is the speaker starts by conceptualising for the topic object in his world model (image 1). Here, obj-307 (obj-91 in the learner's world model) is chosen as topic. In order to help the learner, the tutor conceptualises a meaning for the topic from the perspective of the learner (image 2). For this particular topic and world model the tutor finds the category *left* associated with the word "left" to be most discriminating (image 3). The speaker then utters the word to the learner, who himself has a particular view of the world (image 4). When this is the first interaction ever involving the word "left", the learner does not know the word and the interaction fails. However, after the speaker pointed to the topic, the hearer can adopt the string and connect it to the newly invented projective category *projective-1*. The category derives its angle value from the direction to the topic object (image 5). The initial  $\sigma$  is set to 0.1. This is a low value that focusses the category around the direction of the topic object (image 6).

### Hearer encounters unknown spatial term $s$

Problem: Hearer does not know the term (step 4 fails).

Repair: Hearer signals failure and the speaker points to the topic  $t$ . Subsequently, the hearer constructs a spatial category  $c$  based on the relevant strategy (projective, proximal or absolute) and the topic pointed at (see Figure 2). Additionally, the hearer invents a mapping associating  $c$  with  $s$ .

New words are always adopted in a particular interaction and in a particular context. Angle and distance prototypes are therefore based on the particular distance and angle of the topic of the interaction to the learner. These are never exactly the same distance and angle measured by the tutor and more importantly never the angle and distance of the category used by the tutor. In other words, the learner does not have enough information to guess the category correctly or even near correctly. Consequently, the learners require mechanisms for accumulating information for a particular category over time, in order, to *align* to the category used by the tutor.

Each time a category is successfully used in an interaction

(by the tutor or by the learner), the learner updates the prototype and the sigma of the category. Thereby, the learner aligns his category representation to the tutor. For this he keeps a memory of past distances and angles. For example, projective categories are represented by prototypical angles. After each interaction the learner updates the prototypical angle by averaging the angles of objects in the sample set  $S$  of experiences of the category. The new prototypical angle  $a_c$  of the category is computed using the following formula where  $a_o$  is the angle of sample  $o$ .

$$a_c = \text{atan2} \left( \frac{1}{|S|} \sum_{o \in S} \sin a_o, \frac{1}{|S|} \sum_{o \in S} \cos a_o \right) \quad (4)$$

The new  $\sigma$  value  $\sigma'$  which describes the shape of the applicability function of the category is adapted using the following formula.

$$\sigma'_c = \sigma_c + \alpha_\sigma \cdot \left( \sigma_c - \sqrt{\frac{1}{|S| - 1} \sum_{o \in S} (a_c - a_o)^2} \right) \quad (5)$$

This formula describes how much the new  $\sigma_c$  of the category  $c$  is pushed in the direction of the standard deviation of the sample set by a factor of  $\alpha_\sigma \in ]0, \infty[$ .

The formula for the alignment of distance categories is the following.

$$d_c = \frac{1}{|S|} \sum_{o \in S} d_o \quad (6)$$

$$\sigma'_c = \sigma_c + \alpha_\sigma \cdot \left( \sigma_c - \sqrt{\frac{1}{|S| - 1} \sum_{o \in S} (d_c - d_o)^2} \right) \quad (7)$$

Here  $d_c$  is the new distance,  $\sigma'_c$  the new *sigma*,  $S$  the sample set, and  $d_o$  the distance of an object in the sample set.

### Experiments and Measures

We test the adoption operator in experiments with a population consisting of one tutor and one learner. The tutor is given a part of the English category system. The learner is only equipped with adoption and alignment operators. For the experiments described in this section, tutors and learners share the strategy used for speaking about reality. The tutor and student might be given just the projective strategy or just an absolute strategy. In the latter case the tutor gets all English absolute categories. The learner, on the other hand, gets the means to construe reality using the geocentric wall marker and adoption operators that will acquire absolute categories.

Experiments are repeated 25 times<sup>1</sup>. Each time the learner starts with an empty lexicon and no spatial categories. We measure the success of individual experimental trials using measures defined below.

<sup>1</sup>The runs are not directly performed on real robots but on data previously recorded using humanoid robots. We use a data set of over 800 scenes. A scene always consists of two world models. One for each robot. Scenes differ in number and spatial configuration of objects.

*Communicative Success:* Communicative success is the most important measure as it reflects the overall performance of the population. Every interaction is either a success or a failure. Success is counted with 1.0 and failure is counted as 0.0.

*Number of Categories:* This measure simply counts the number of categories known to the agent. It is therefore a measure of variation. Typically one would also count the number of constructions (category-word mapping) an agent has. But in the acquisition experiments described in this paper the mapping is essentially one to one. For every category, there is precisely one construction.

*Interpretation similarity:* This is a measure tracking how similar the interpretation of each word known to the tutor is to that of the learner. For this the categories attached to the word both in the tutor and the learner are compared. We model projective categories by means of a direction and an applicability function width parameter  $\sigma$ . Hence, two categories are most similar when both angle and  $\sigma$  are equal. The precise formula is based on the repertoire of words  $w \in W(t)$  known to the tutor  $t$  and the applicability of the category  $C(t, w)$  the tutor associates with word  $w$  to the category the learner  $l$  associates with that word  $C(l, w)$

$$I(t, l) = \frac{1}{|W(t)|} \sum_{w \in W(t)} s(C(l, w), C(t, w))$$

If the learner has no category associated with a particular word  $w$ , hence, when  $C(a_{tut}, w)$  does not find a category the applicability is 0. If, however, the learner has a category associated with the word then  $s$  is defined as follows (e.g. for angle-based categories)

$$s(c, c') = e^{-\frac{1}{2}(a_c - a_{c'})^2 \frac{2}{\sigma_c + \sigma_{c'}}}$$

## Experimental Results

Figure 3 shows aggregated dynamics of 25 experimental runs testing the acquisition of projective categories. The learner quickly reaches communicative success which means he can act successfully as hearer and speaker after 25 interactions. He learns all categories from the tutor (in this case the four spatial categories).

Figure 4 shows how the alignment operator makes categories evolve over time (same category as in Figure 2). The categories of the learner become aligned with the operators of the tutor over time. This is also apparent from the dynamics of the interpretation similarity measure.

Naturally, alignment and adoption operators have a number of parameters, for instance how many samples to consider, how eager to update the  $\sigma$  component using  $\alpha_\sigma$  and so on and so forth. We have tested the impact of these parameters by doing many repeated experiments with different parameter settings (results not shown for space reasons). We can show that these parameters are quite robust and small changes do not affect the overall performance of the system.

## V. SIMULTANEOUS ACQUISITION OF VARIOUS SPATIAL SYSTEMS

In the experiments just described, there is only a single category system at work. Learners are acquiring either a

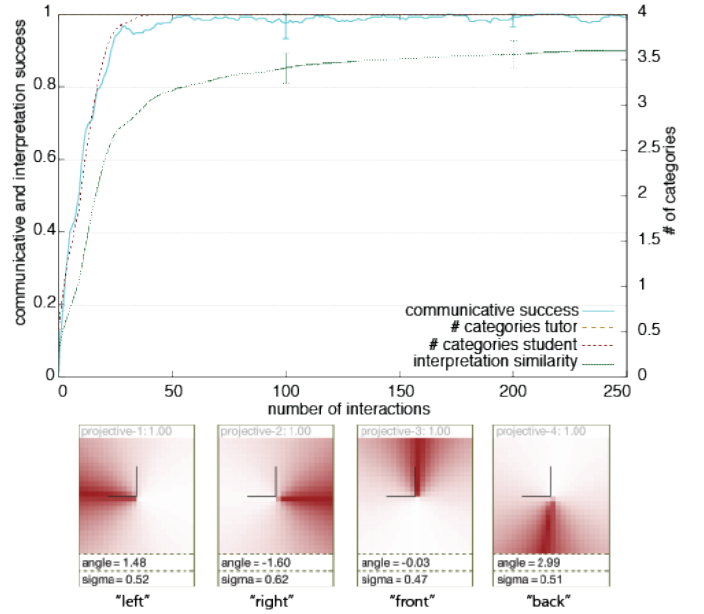


Fig. 3. The top figure shows the dynamics of acquisition experiments over 250 interactions (25 runs averaged) in which a learner is trying to acquire the projective language system from a tutor. Agents quickly reach communicative success (the base line experiment of tutors communicating reaches approx. 98% success for the same data set). After roughly 25 interactions, all categories and their corresponding strings have been adopted (the number of categories approaches 4) In the remaining interactions the alignment operator drives the *interpretation similarity* towards 1.0 (which is the highest value and signifies total overlap between the categories of the tutor and the learner). Interestingly, communicative success correlates with the number of categories of the student more than it does with interpretation similarity. This shows that agents do not need perfectly aligned categories to be able to communicate successfully. The bottom figure shows the categories acquired by a learner in one particular population of an acquisition experiment and to which strings they are linked. The resulting categories are very similar to the projective categories given to the tutor.

projective, an absolute, or a proximal system. Obviously this is a limitation of the model and the experiments. Human students of English are learning multiple systems more or less at the same time. At least students are confronted with different systems at the same time.

Suppose a tutor is given the three strategies: projective, proximal and absolute. Suppose further that the learner agent in such conditions hears a new term, for example, “near” from the tutor. The learner faces a problem. He has no a priori means of knowing whether this term is part of a projective, proximal or absolute strategy. What is necessary to allow artificial learners to cope with a situation where there is uncertainty about the strategy used by the tutor? One possibility often discussed in the literature on language is to use discrimination as a means to decide between various conceptualisation strategies. We know from discourse theory that language users are maximally cooperative and choose most discriminating strategies in verbalisation [16], [17]. These facts have also been confirmed for spatial language [18]. A way for a student to decide which conceptualisation strategy underlies an unknown term is to see which strategy is most discriminating.

Figure 5 gives a graphical explanation of the process. Upon hearing a new word, the learner invents for all conceptualisation strategies. Each of these inventions will lead to a potential



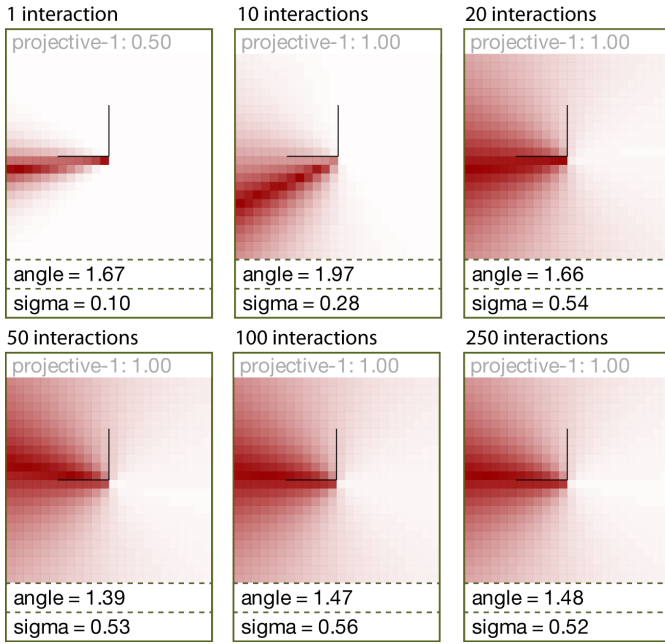


Fig. 4. Development of the projective category whose initial adoption is depicted in Figure 2 over many interactions (after 1, 20, 50, 100 and 200 interactions). In the beginning the width of the category is narrow (small  $\sigma$ ). Gradually its direction approaches the direction of the target category `left` and so does its  $\sigma$  (the target category's  $\sigma$  is 0.4).

candidate category. The learner tries each of these categories in his current world model and computes a discrimination score. The learner only keeps the category which is most discriminating. Discriminative power of candidate categories is ranked via scores. The score is based on the similarity of a particular category with the topic object and the difference of that with the similarity score of other (distractor) objects in the world model. Agents choose the candidate category with the highest score.

$$\text{disc}(c, t) = \text{sim}(c, t) - \max_{o \in C/t} (\text{sim}(c, o)) \quad (8)$$

where  $c$  is a candidate category and  $t$  is the topic object.

Figure 6 shows results for the simultaneous acquisition of proximal and projective categories. The learner quickly acquires the target system (near, far, north, south, east, west). Similar results can be obtained for the simultaneous acquisition of proximal and absolute categories.

Discriminative power is not a perfect “guessing” mechanism. The reason is twofold. First, the experiments are grounded. Robots frequently make different distance and angle estimations of the same object. This can make the learner guess the wrong strategy because discrimination scores rely on perceived angles and distances. Second, tutors have a fixed category system which has very particular distances and angles encoded in category prototypes. For example, the `left` prototype is exactly at 90 degrees. The learner though will guess a category based on the distance and angle to the topic which is never directly aligned to 90 degree angles. Consequently, similarity and therefore discrimination score are different functions for tutor and learner.

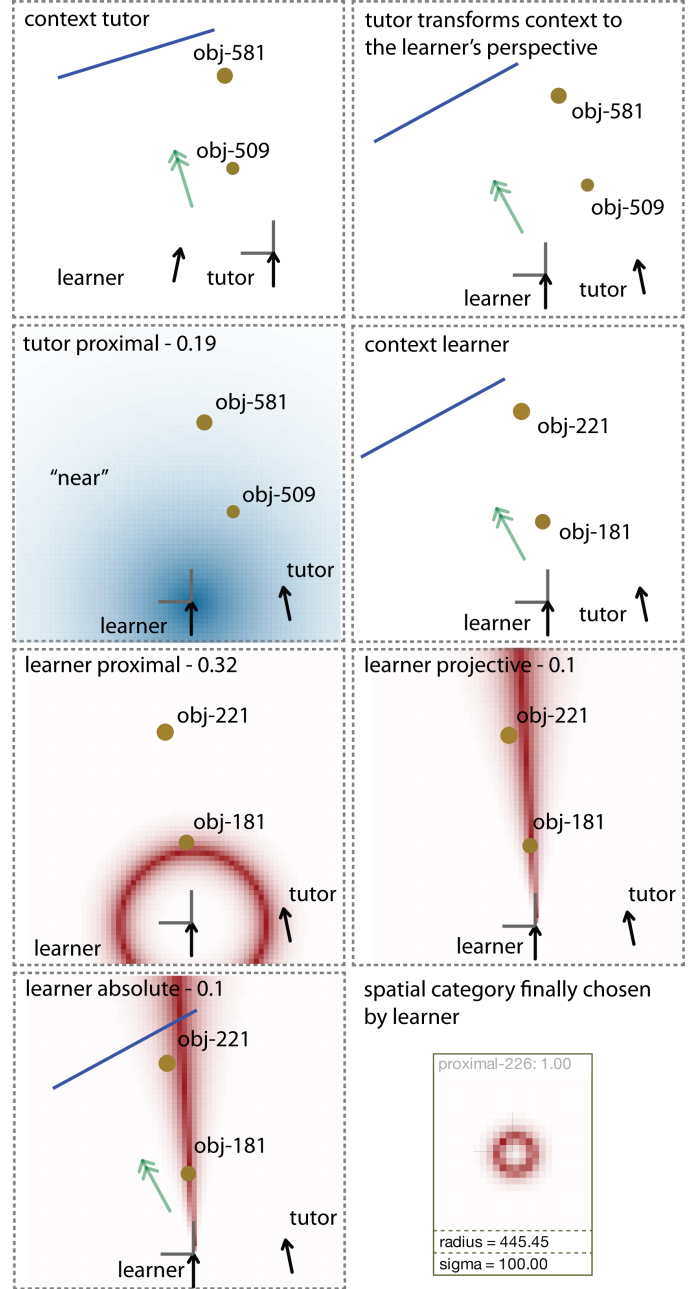


Fig. 5. Inference by the learner in re-conceptualisation (after receiving pointing from the speaker) as to which category type was used by the tutor (speaker). The steps are the same as for proximal, projective and absolute category adoption. However, instead of just adopting one category, the learner will build three categories for the topic object. Each of these categories has a particular discrimination score. The learner chooses to store the category with the highest discrimination score. Here the invented proximal category wins (score 0.32). It is the category that will be linked to the word “near”.

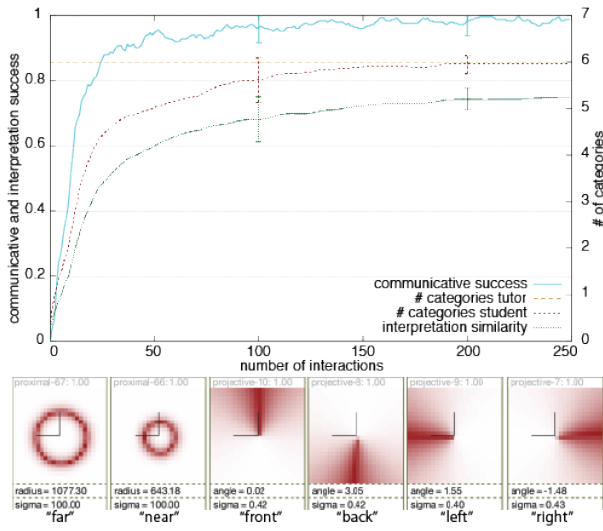


Fig. 6. Results of acquisition experiments using inference. The tutor is equipped with proximal and projective categories.

Obviously, for discrimination to work, there needs to be sufficient discriminative difference between strategies. Otherwise, learners have no means of deciding between different strategies in particular interactions. This limitation already plays out with the spatial systems discussed in this paper. There are two angle-based strategies: projective and absolute. Here discrimination fails because as can be seen in Figure 5 both strategies have the same discrimination score (0.1). As a consequence experiments where learners have to acquire the projective and absolute system at the same time additional mechanisms are needed.

Such mechanisms can be biases or other information that clearly distinguish between system. For instance, absolute and projective could be treated differently in the grammar (not the case for English). Also, the English absolute system is much less frequently used for referring to objects in the immediate surroundings of interlocutors, and it is tied to particular measurement devices such as compass or sun position estimation. In other words, to learn the absolute system requires to understand particular human technology. Something not modelled here.

## VI. CONCLUSION

The most important result of this paper is to show how to go from single strategy acquisition to a system that can acquire multiple category systems at the same time. This is an important result and it shows the potential for scale up, particularly with respect to grounded systems that learn from increasingly unconstrained data.

This paper detailed a number of experiments exploring the acquisition of spatial language by grounded, artificial agents. Through the proposed learning operators (adoption and alignment), learners were enabled to successfully acquire different target systems. Ongoing and future research is building on the results presented in this paper and extends them to grammar and complex semantic structure acquisition in interactive scenarios.

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